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Research Article

CROWD DYNAMICS ANALISYS: SIMULATING HETEREOGENEOUS CROWDS WITH PANIC EFFECT STOCHASTICS BEHAVIOUR

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ABSTRACT

In a crowd, where the density might reach one person per square meter and above, the mass of individuals moves in a way that may potentially induce panic amongst individuals, or hazards of personal injuries, from slight to fatal. A computer simulation is implemented and conducted in order to study and analyze the dynamics and behavior of crowds, both at micro- and macro-levels. The simulation is comprised of multiple arenas with different layouts, as well as different compositions of heterogeneous agent behavior. The simulations are observed to conform to established results on a localized scale, and the statistical data shows no significant increase in total evacuation time with increasing composition of non-interactive, path-finding agents amongst flocking agents.

Keywords: crowd dynamics; multi-agent simulation; swarm; emergent behavior

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1. INTRODUCTION

Crowd dynamics refer to the interaction the macro-level patterns of movement of a large number of people within a high-density environment, and the micro-level interactions of individuals or entities within the crowd. A high-density environment, in this case, refers to environments where crowds form and move above the critical density of more than one person per square meter [1]. At such densities, there is potential for overcrowding and personal injury [1]. Despite the potential hazards, crowd dynamics and psychology are considered a field where only a little literature references were made to outdated work from past decades or even centuries [2].

One of the reasons is that crowd behavior is difficult to observe and simulate, particularly under dire emergencies, which cannot be tested unless a real crisis occurs [1]. It is neither feasible nor ethical to expose members of the public to real emergencies in order to analyze their behavior and reactions [1], only to take corrective actions thereafter.

In order to analyse the problem, computer simulations are turned to as an alternative [1]. Pedestrian simulation has received important attention in the context of crowd evacuation management and panic situation analysis [3]. Complex models have been proposed and compared to crowd dynamics in real life, including continuum crowd flow [4-6], cellular automata [7-9], and multi-agent systems [9-14].

Many simulations on heterogeneous crowds in the past, may conform to established results in pedestrian dynamics, but the behavior of heterogeneous crowds under emergency egress, where each member of the crowd has the same set of predetermined destinations has yet to be explored thoroughly. A study that combined the systemic effects of panic towards crowd dynamics and heterogeneous crowd composition would help alleviate the problem and shed some insight on the study of crowd egress under emergency situations.

This article studies and simulates the dynamics of a crowd of people under evacuation using multi-agent simulation approach. The simulation tool used in this work, NetLogo 5.1.0, is a multi-agent programming language and modelling environment for simulating natural and social phenomena, designed for both research and education across a wide range of disciplines [15-16].

This work focuses on a crowd model which having two types of agent; namely *tenant* and *visitor*, occupying an enclosed arena. Agent *tenant* represents a tenant in a particular arena and assume to be a well-trained agent that knows the environment of the arena. Agent *visitor* represents a visitor to that particular arena, and assume to be having zero-knowledge about the arena. The model is then simulated and the macro-behavior of the crowd is analyses and study in depth.

2. AGENT BEHAVIOR MODELING FRAMEWORK

From the previous section, it can be seen that there is only one past work that focused specifically on combining the study of panic evacuation of large, heterogeneous crowds [14]. Therefore, in order to lay down the groundwork for simulating these particular scenarios, a basic, simplistic approach towards modeling and simulating the crowd dynamic has been taken, without compromising the conformity to established results.

In this work, agent-based modeling approach is used towards modeling the behavior of individuals within a heterogeneous crowd that is a composition of different types of homogenous agents. In agent-based modeling, the macro-level crowd dynamics emerge from the micro-interactions between agents, which are in turn results of the individual behaviors of each interacting agent. Therefore, this section is discussing on previous studies done on modeling behaviors of agents in a swarm.

2.1 Flocking behavior in pedestrian crowds

Flocking behavior is used to describe the collective behavior of a large group of mobile agents with a common group objective, such as safety in numbers from predator [17]. Flock behavior is often observed in nature, where examples of flocking agents include birds, fishes, and insects [18]. Reynolds [19] introduced three heuristic rules that has to the first computer animation of flocking, they are:

a) Alignment rule: Attempt to match speed and heading with nearby flockmates;

b) Cohesion rule: Attempt to stay close to nearby flockmates;

c) Separation rule: Avoid collision with nearby flockmates.

However, being subjective to broad interpretation, which complicates the objective analysis and implementation of these rules [18]. Multiple mechanisms and models were reviewed by Olfati-Saber [18], including the work of Toner and Tu [20] as well as Vicsek [21]. The study and applications of flocking behavior were presented in multiple fields of discipline [22-27], including that of pedestrian crowd movement and behavior [6,26-27]. Due to the simplicity of the technique [23], flocking behavior is suitable for modeling and simulating large number of agents in high spatial densities.

2.2 Path-finding algorithms

Given a destination and a starting location, there are multiple developed algorithms which can be used for a computer-generated mobile agent to find a non-colliding path in between. Some of the examples include the Dijkstra algorithm, the Greedy path-finding algorithm, and the $A*$ algorithm [28,29]. In Dijkstra's algorithm, all neighboring nodes or locations were assigned a path value, $g(n)$, depending on the distance from the starting location, or the time required traveling to the patch from the starting location. Obstacles will be marked as non-traversable with a path value of infinity. The goal is then to find a shortest path between the starting location and the destination without doubling back along the way.

In Greedy path-finding algorithm, the path is constructed by assigning a locally optimal value, $h(n)$, based on the estimated distance between the choice node and the destination node, and updating the path with every sweep. This heuristic approach allows quicker search time as compared with Dijkstra's path-finding algorithm, but the resultant path is longer as the Greedy algorithm cannot predict obstacles beyond the local search range and thus may have to double back along the path.

$A*$ algorithm is a variation of Dijkstra's algorithm, which assimilates the heuristic approach of Greedy algorithm [28]. When sweeping for a shortest path, $A*$ calculates heuristic values, $f(n)$, based on both Dijkstra's cost from starting point and Greedy's heuristic estimated cost to destination, ignoring explored nodes that proved to have a higher heuristic values. $A*$ algorithm is a popular path-finding algorithm in applications such as video games [30], robotics [28] and computer simulations [29], although the algorithm suffers mainly from the drawback of processing time when computing paths for large number of agents across complex arenas [29].

2.3 Effects of panic towards crowd dynamics and behaviors

Panic has been historically studied in the field of social psychology as a form of collective behavior under situations where resources are dwindling or already scarce to begin with [13,31]. Panic has been recorded to result in maladaptive behavior that spreads throughout the crowd [31], such as crowd congestion and stampedes. Helbing *et al*. [13,32], with all references therein, has provided valuable insight on documentation of characteristic features of panic in crowds, despite the lack of quantitative theories predicting crowd dynamics with panic behavior.

However, Helbing *et al*. [13,32] did not account for heterogeneity within the crowds, which may include individuals that are able to resist the effects of panic to varying degrees, or may even be capable of aiding neighboring individuals to achieve the same. This will be one of the main focal points in this work, to study if the micro-behavior of such agents may influence the macro-dynamics of a crowd in panic, and to analyze if such findings may reflect realistic scenarios of egress.

3. AGENT BEHAVIOR SIMULATION SETUP

3.1 Working arena

Simulation has been developed using NetLogo 5.1.0, attempting to replicate the behavior of crowds under egress using flocking behavior and $A*$ path-finding algorithm.

The simulation interface is set up as shows in figure 1. The arena where the evacuation simulation is to be carried out, or the simulation world, is the black-colored window on the right. The world-wrapping option is disabled for the arenas such that agents may not cross any edge of the world and reappear on the opposite edge.

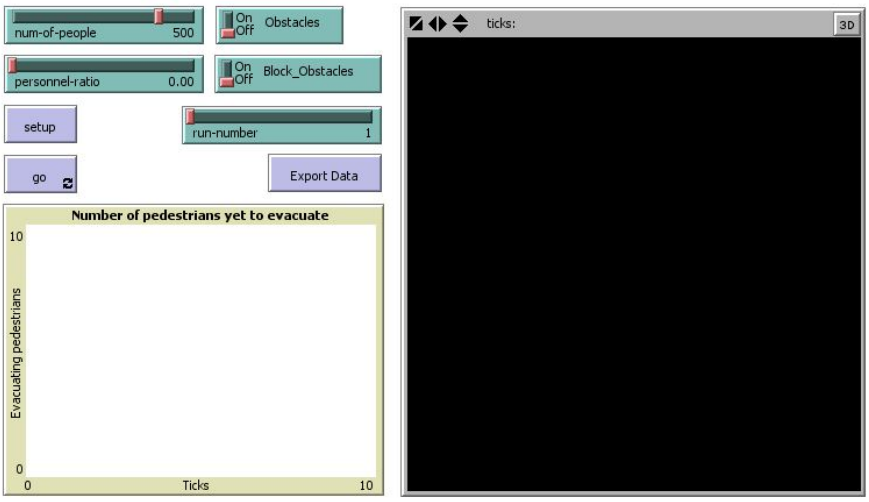
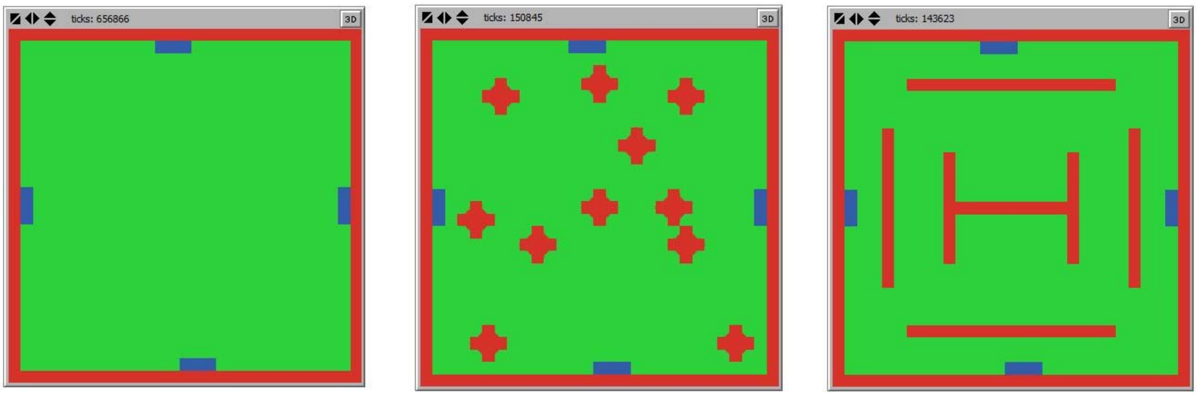


Fig.1. User interface for crowd simulation

The world is set as a square-shaped arena with a total length of 29 patches a side, where each patch is given a set of integer planar coordinates in the *xy*-plane from (-14, -14) to (14, 14). Figure 2 shows the arena for simulation; where blue patches are the exits from the arena, green patches refers to flat traversable terrain, and red patches are non-traversable obstacles. Three different types of arenas were tested in the simulation, one without any static obstacles (figure 2a), one with blob obstacles (figure 2b), and one with block obstacles (figure 2c).



(a) Open-arena (b) Blob-arena (c) Block-arena

Fig.2. Evacuation arena for simulation

3.2 Agent behavioral design

Two types of agent behavior were designed for simulation as depicts in Table 1. *Tenant* agents have global knowledge of the evacuation arena layout, including the nearest exits and all static obstacles in the arena. *Visitor* agent on the other hand, refers to agents that only have local line-of-sight; which is the area of a cone with an 80-degree arc and a radius of 3 to 5 patches ahead of the individual agent. *Visitor* agents also do not know the layout of the whole evacuation arena. The behavioral models for both types of agents are illustrated in Appendix A and Appendix B respectively.

At the beginning of the simulation, 500 agents are evenly distributed in the arena. *Tenant* agents will then find a path towards the nearest exit by applying the *A** algorithm, accounting only for all static environmental obstacles. When encountering other agents in the path, *Tenant* agents will remain at their patch until the patch forward is cleared before moving on towards the exit. Due to constraints in computer processing, *Tenant* agents will only apply the *A** path-finding algorithm at the start of the simulation without accounting for dynamic obstacles, and will not apply brute force recalculation every time an obstacle is encountered along the path.

Table 1: Agent's knowledge design for simulating heterogeneous crowd

Agent type	Knowledge
Tenant	Knows the global layout of the arena; knows the shortest route to the nearest exit
Visitor	Knows only within it's vicinity (80-degree arc, 3 to 5 patches ahead)

As for *Visitor* agents, they will first attempt to follow *Tenant* agents, using *A** algorithm to find a path towards the location of the nearest *Tenant* agent. In the absence of *Tenant* agent in the line of sight, *Visitor* agents will apply the alignment rule of flocking behavior to head towards the exit, if no panic behavior is exhibited. *Visitor* agents that exhibit panic behavior will not apply flocking behavior, instead moving towards any nearby empty patch in an individual search for exit.

Even when flocking, *Visitor* agents will always be moving to a nearby empty patch if it is unable to move towards the destination due to an obstacle in front of it, which may be static, environmental obstacles, such as pillars and walls; or dynamic obstacles that include other mobile agents. When moving to a nearby empty patch, *Visitor* agents will prioritize empty patches that are right in front of them within an 80-degree arc, then empty patches within a 180-degree arc in front of them, before considering patches behind them.

Both types of agents have the same objective – that is, to evacuate from the arena. Therefore, both agents will move towards the exit, overriding all other behaviors, if the exit is within line of sight. The panic behavior is introduced only to Visitor agents, with random occurrence that increases exponentially in probability as more time passes in the simulation.

3.3 Simulation and data collection

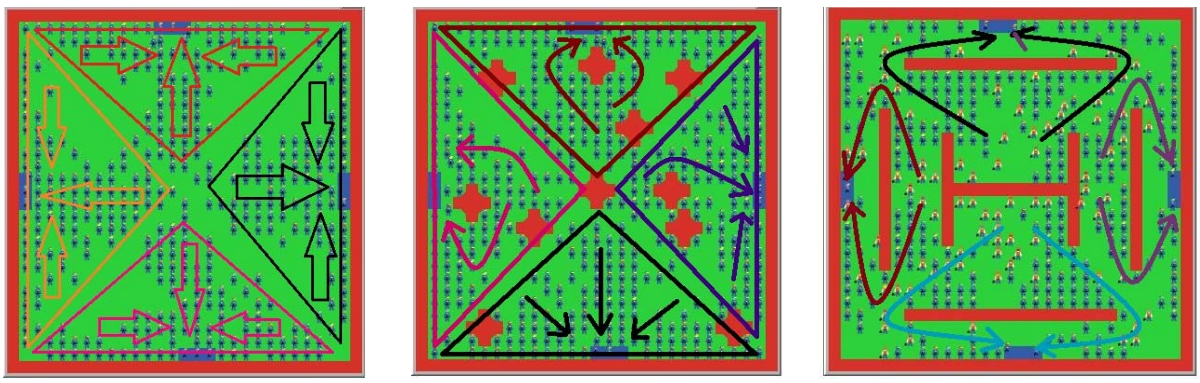
For each arena, 500 agents are distributed evenly. Simulations are done by varying the percentage of *Tenant* agents existed in the arena, *i.e*. 0%, 25%, 50%, 75%, and 100%. For each set, a total of 20 simulation runs are conducted to provide a sample size large enough for precise analyses. The number of agents remaining in the arena over time – measured in ticks (simulation time) – is tabulated with records at 10-tick intervals, and the average number of agents remaining over time are plotted for each simulation set. The standard deviation distribution for each interval is also calculated and analyze in an attempt to interpret the emergent crowd behavior. Finally, the results between the simulation sets are compared in order to discern a trend between arenas as well as ratio of heterogeneous agents.

4. RESULTS AND DISCUSSION

4.1 Emergent crowd behavior

For *Tenant* agents, a discernible pattern was observed. Since *Tenant* agents only used the *A** algorithm to find a path to the exit during the setup stage of the simulation, and follow the path to the exit, the results are that all *Tenant* agents of a region follow the same path towards the nearest exit, depending on their starting location. Such behavior is expected from a coordinated, organized evacuation, although further work is required to verify the observation.

The overall dynamics of crowds consisted of *Tenant* agents are as illustrates in figure 3, where a *Tenant* agents within the same regions follow not just the same general direction, but the exact same Euclidean shortest path towards the exit. The result is that approximately straight queue lines appeared during the evacuation of multiple *Tenant* agents heading towards the same exit, resulting in non-optimized space further away from the exit, shows as empty patches in figure3.

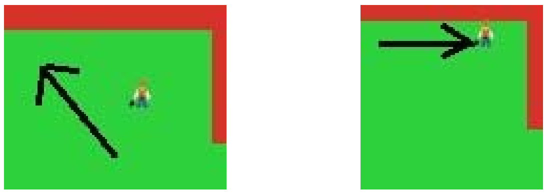


(a) Open-arena (b) Blob-arena (c) Block-arena

Fig.3. Path taken by *Tenant* agents towards the nearest exit in simulation arenas

For *Visitor* agents, the observed resultant behavior is much more chaotic. Without being pre-programmed to bias towards left/right side, and with the presence of random generated panic effects, *Visitor* agents were observed to follow a dynamic path that is altered by neighboring agents as well as any obstacles in the path ahead. When faced with an obstacle ahead, a *Visitor* agent, without any external influence, is liable to take any path with the line-of-sight to avoid the obstacle.

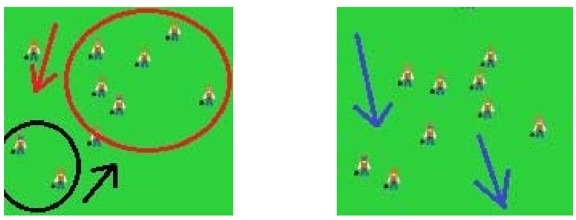
When taking an alternative path to avoid the obstacle directly in front of them, *Visitor* agents face the adjacent path before moving towards it, and it is observed that such a turning before moving is capable of influencing the heading of neighboring agents. As shows in figure 4, the single Visitor agent turned right as a consequence of random choices when it reached the obstacle (red wall) in front of it, despite the fact that it will lead to another obstacle in the form of a corner.



(a) (b)

Fig.4. One of many examples of direction taken by a single *Visitor* agent: (a) before reaching the horizontal wall; (b) after reaching the horizontal wall

The herding behavior programmed into *Visitor* agents does allow individual agents to follow the flow of the crowd, merging into one group with a new heading. Shows in figure 5a, one group of *Visitor* agents, circled in black with their headings in the direction of the black arrow, met a second group circled in red, and the resultant merged crowd reoriented towards the direction of the blue arrows in figure 5b.



(a) (b)

Fig.5. One of many examples of direction taken by groups of *Visitor* agents: (a) before merging with different headings; (b) after merging into a single crowd with the same heading

But, two groups of *Visitor* agents of similar sizes may significantly alter each other's original headings. Futhermore, due to the limited area-of-sight for *Visitor* agents, the emergent crowd dynamics are localized, and during the simulations, there were no observed global crowd patterns where the majority of the agents are *Visitor*.

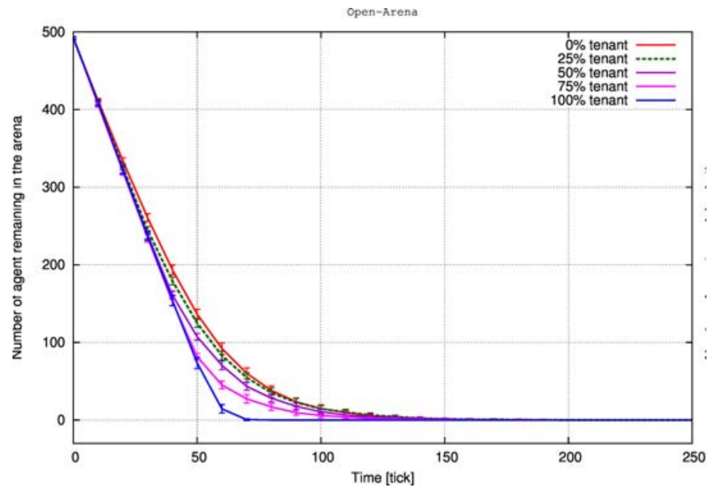
4.2 Analysis of evacuation time

A total of 20 simulation runs for each set were carried out and sampled as stated previously. The average evacuation time [tick], and standard deviation σ of the time taken to facilitate complete evacuation are calculated and tabulated in Table 2. The results of the parametric sweep are sorted by the ratio of Tenant agents, and by the layout of the simulation arena in figure 6. In figure 6, the average number and standard deviation of agents that had yet evacuated are plotted over 10-tick intervals.

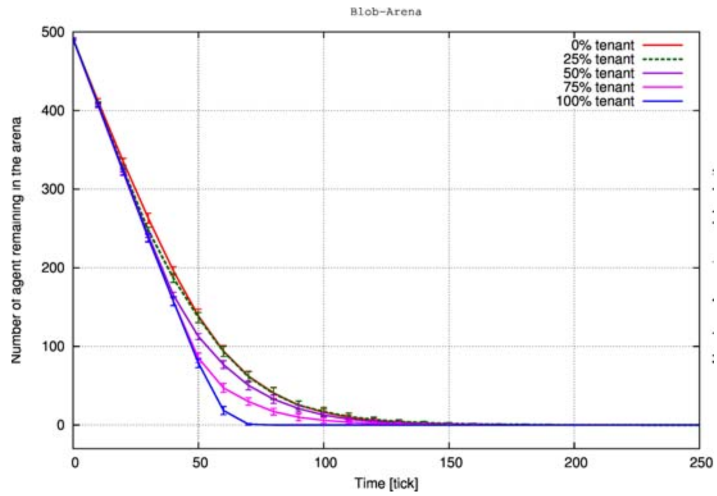
Table 2: Average evacuation time [tick], and standard deviation, σ for 20 simulation runs per simulation set

		Percentage of *Tenant* in the arena				
Arena type	**Description**	**0%**	**25%**	**50%**	**75%**	**100%**
Open-arena	Average evacuation time [tick]	174.5	174.5	153	153.5	72
	Standard deviation σ	34.8644	25.0210	19.4936	23.2322	4.104
Blob-arena	Average evacuation time [tick]	163.5	180	152	152	75
	Standard deviation σ	22.1980	28.6540	20.6729	35.7771	5.13
Block-arena	Average evacuation time [tick]	320.5	301.5	287	232.5	114.5
	Standard deviation σ	27.8104	45.6848	47.8044	43.6342	7.592

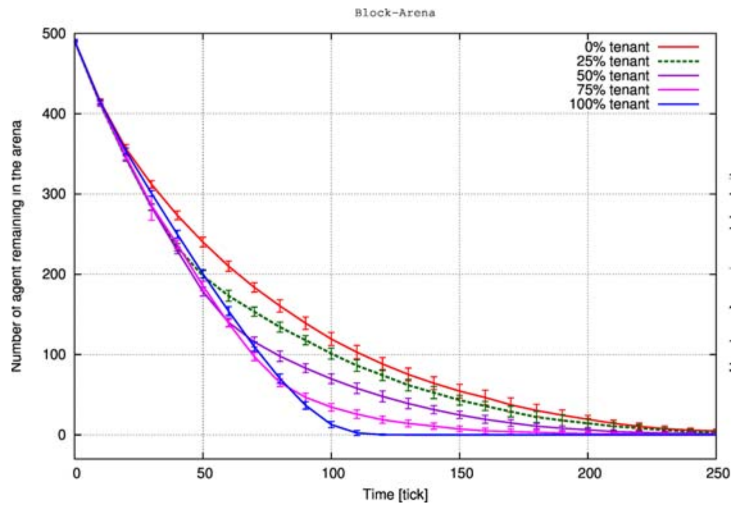
From Table 2 above, it can be inferred that simulations in arenas with complex block obstacles take significantly less time to complete evacuation only when the *Tenant* agent composition is 50% or higher. For other arenas, increasing *Tenant* composition does not result in significantly quicker time taken for complete egress simulation, until all 100% of the agents are *Tenant*. Simulations with higher *Tenant* agent composition only facilitated quicker egress during the early stages, when all *Tenant* agents head along the path towards the exit simultaneously.



(a)



(b)



(c)

Fig.6. Average number of agents not yet evacuated over time for heterogeneous agent ratio with varying arena layouts: (a) Open-arena, (b) Blob-arena, (c) Block-arena

As can be seen in figure 6, there is no significant difference between time taken for complete evacuation between open-arena and blob-arena, only between the former two arenas and the arena with block obstacles. Given the same heterogeneous agent ratio, arenas with block obstacles consistently require 50% to 95% more time to completely evacuate compared to arenas with blob obstacles, or open arenas without any obstacles at all.

The reason behind the phenomenon may be explained by the lack of interaction between the two agent types. While *Visitor* agents were set to seek out and follow *Tenant* agents within local line-of-sight; *Tenant* agents were not set to help facilitate efficient egress by actively leading neighboring agents towards the exit, instead progressing solely along paths determined at the beginning of the simulation.

If a form of behavior been implemented into a third agent type that actually seeks out and helps facilitate other agents' egress, the difference between the egoistic and altruistic behavior in different agent types and their composition within the crowd may provide an insight towards modeling and observing the effects of the aforementioned different approaches in crowd evacuation.

The complexity in arena layout, coupled with the lack of efficient path-finding algorithms in *Visitor* agents, contributed to the phenomena where *Visitor* agents are often "trapped" between the inner walls of the block-obstacle arena for extended lengths time, resulting in longer time taken for complete evacuation. It can be hypothesized that higher densities in layouts of blob obstacles, different layouts of block obstacles, or a combination of both factors will be able to model the results of evacuation in different arenas more realistically.

5. CONCLUSION

An emergency egress agent-based model is implemented and tested using NetLogo 5.1.0 as the programming and modeling platform. The model is capable of generating complex arenas, integrate heterogeneous rules into a crowd of mobile agents, and visually simulate emergency evacuation from the arena under preset parameters. Two different sets of behaviors are modeled into the mobile agents, the first being a variant of the *A** path-finding algorithm, and the second being the three rules of flocking behavior.

During simulations under the sets of coded rules, observation is made possible for the micro-level interaction between agents and the environment, and macro-level crowd patterns on a localized scale. Agents with the intelligent $A*$ path-finding algorithms are observed to head directly towards the exit with optimum efficiency while flocking agents are found to take more time to facilitate egress. The model was tested to collect statistical data, and the results were found to be insignificant. That is, no significant decrease in evacuation time has been observed for a non-substantial increase in agent composition with intelligent path-finding behavior.

Two main limitations of this project have been found during the subsequent analysis of the results for the project. The first is the constraints set by the computer processing power required to implement the $A*$ algorithm over a large number of agents. Given the algorithm's approach to search for, and only accept, globally optimal heuristic values, it requires much processing power and time, and thus can only be implemented during the initiation phase of the simulation. As a consequence, the existence of mobile obstacles such as other agents present along the path is not taken into account, and the path is not recalculated when the agent encountered mobile obstacles on the path towards the exit.

The second limitation was the lack of hard-coded interactions between the two types of agents present within the heterogeneous crowd. The individual-level interaction has shown to be unidirectional only, as flocking agents looked to follow the path-finding agents towards the exit. But, the reciprocal interaction was not implemented, therefore a small increase in the numbers of path-finding agents was found to be insignificant towards reducing the total time taken for complete egress.

Further work may be done by introducing more types of agents into the simulation, to further enhance the heterogeneity of the crowd in simulations. More complex behavioral rules, such as codification of interaction behavior between agents, both egoistic and altruistic, may be implemented to observe the effect of altruism and egoism in emergency egress. A simpler approach towards the implementation of intelligent path-finding algorithms is recommended to reduce the required processing power and enable the simulation of path recalculation. Finally, more case studies should be observed and other models should be developed in order to compare the emergent crowd behavior and to ensure that the observations conform to realistic evacuation phenomena.

6. ACKNOWLEDGEMENTS

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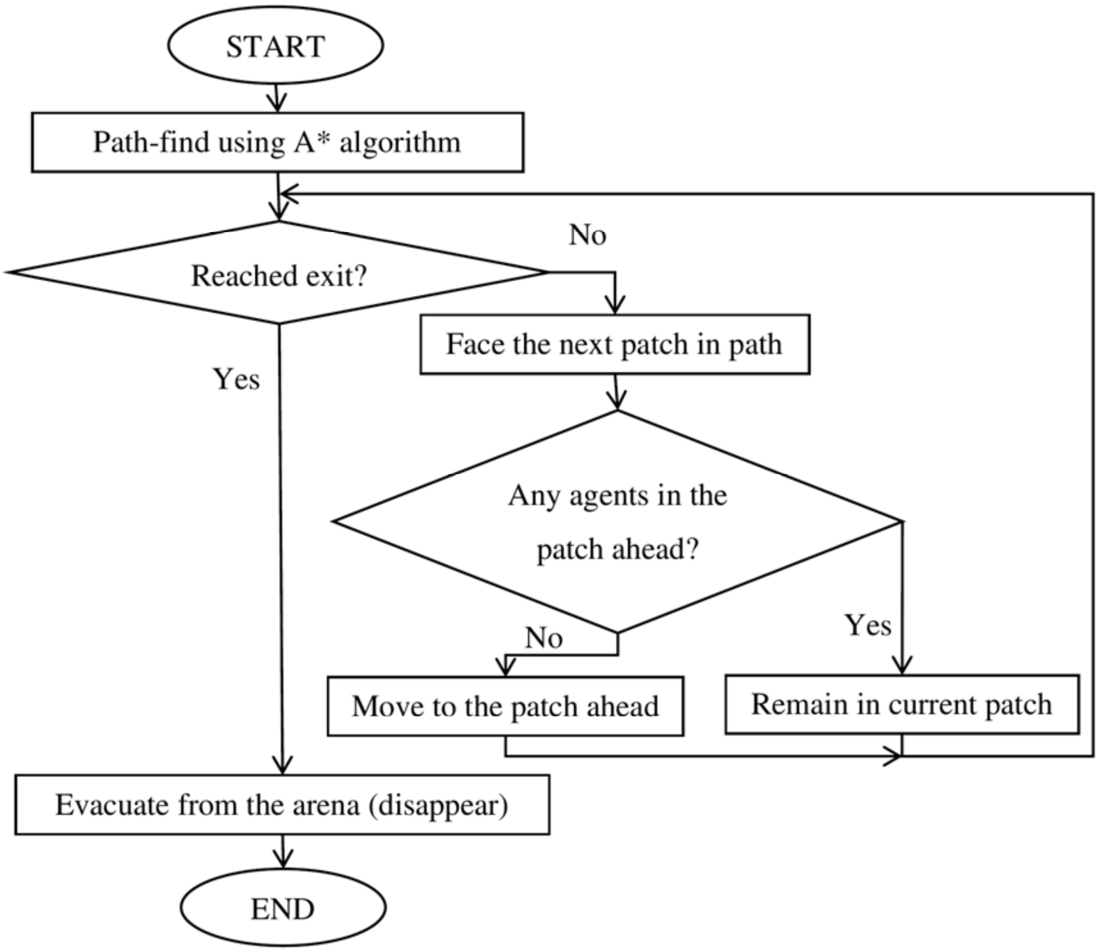
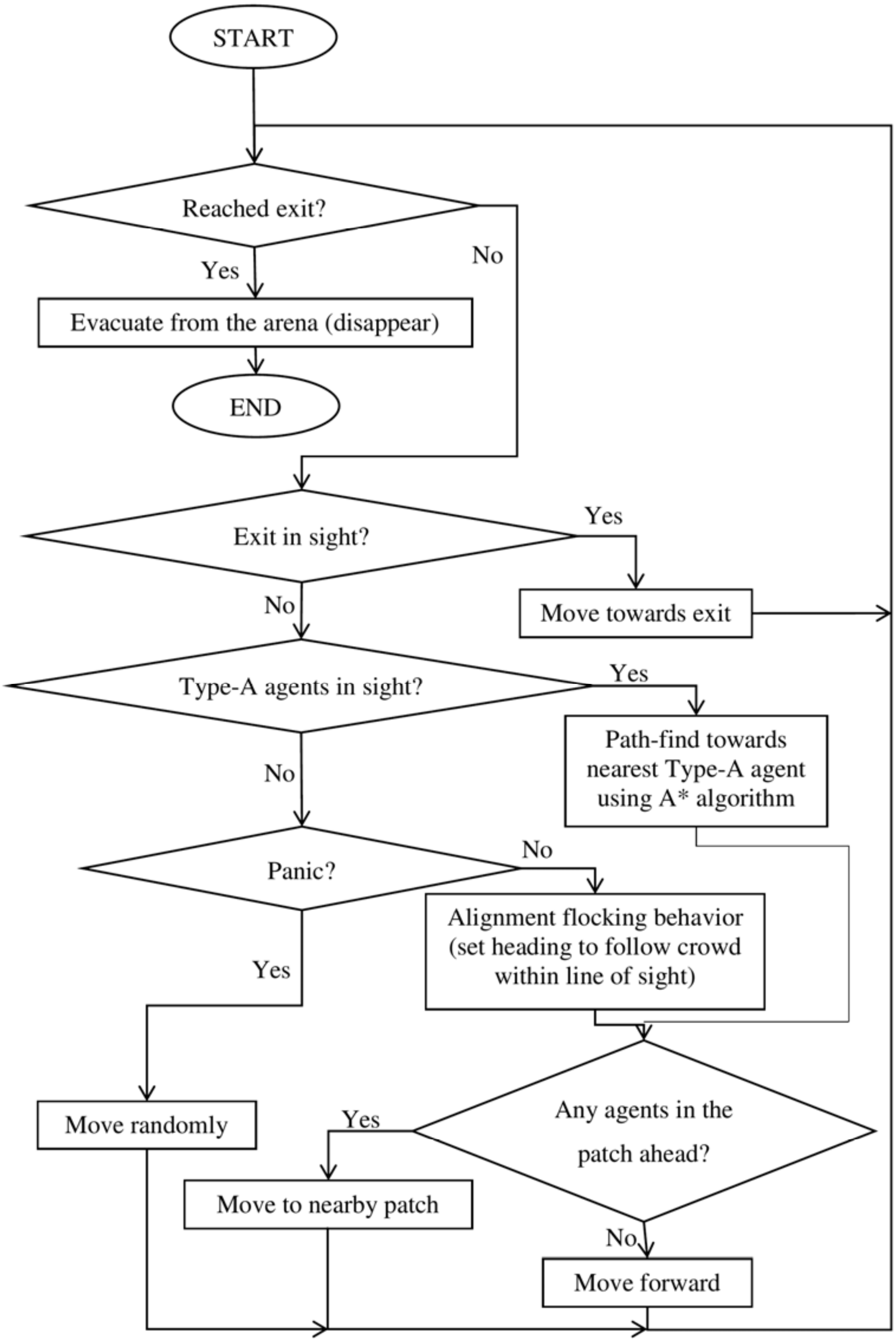
APPENDIX A

Flow chart for behavioral model of *Tenant* agent



APPENDIX B

Flow chart for behavioral model of *Visitor* agent



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